DOI:
10.1016/j.ssresearch.2018.06.001

Document Version
Peer reviewed version

Link to publication record in King's Research Portal

Citation for published version (APA):
Rhead, R., Elliot, M., & Upham, P. (2018). Using latent class analysis to produce a typology of environmental concern in the UK. *SOCIAL SCIENCE RESEARCH*, *74*, 210-222.
https://doi.org/10.1016/j.ssresearch.2018.06.001

Using latent class analysis to produce a typology of environmental concern in the UK

Abstract

Factor analysis is often used to study environmental concern. This choice of methodology is driven by predominant theories that tie environmental attitudes to the multidimensional construct of environmental concern. This paper demonstrates that using a clustering method such as latent class analysis can be a valuable tool for studying environmental attitudes as they exist within a given population. In making the case for the value of latent class analysis in this context, we examine UK public concern for the environment and how this concern is associated with pro-environmental behaviours. To do this we use responses to DEFRA's 2009 Survey of Public Attitudes and Behaviours towards the Environment, which is still the most nationally representative survey of its type in the UK. Grouping respondents according to homogenous response patterns, we identify four classes of people, defined by their concern for the environment: *Pro-environment*, *Neutral Majority*, *Disengaged* and *Paradoxical*. To understand how these attitude classes are associated with behaviour and socio-economic status, class membership probability is regressed onto education, income and social grade, as well as 16 measures of environmental behaviour related to transport, food, recycling and home energy conservation. The results contradict most previous research with the environmental attitude classes by being highly predictive of environmental behaviour.

1. Introduction

Categorising or grouping people on the basis of shared attributes is common in popular parlance and indeed in the social sciences generally (Van Gaalen and Dykstra 2006; Nylund et al. 2007). For environmental psychologists, a more common method for analysing environmental attitudes is factor analysis. The suitability of this approach rests on latent attitudes being meaningfully linear and hence continuous at a conceptual level. However, a case can also be made for segmentation, using cluster analysis or latent class analysis (LCA). Segmentation treats latent constructs as categorical rather than continuous, and this can be parsimonious when capturing variance within (and describing) a population.

There is a small but developing body of work in environmental psychology based around LCA. Hence, for example, Ehrlich et al. (2016) use LCA to investigate the extent to which heterogeneous perceptions and opinions toward water resource policy influence recreational demand in a river basin and the associated valuation of ecosystem services. LCA revealed two distinct groups of respondents that differ in their perceptions and opinions, despite similar demographic characteristics. Similarly, Steiner, Peschel, and Grebitus (2017) use LCA to differentiate segments of ecologically-oriented consumers from price-sensitive segments, in the context of response to carbon emission and water-consumption labelling. López-Sánchez and Pulido-Fernández (2016) use LCA much as we do here, to identify qualitatively-labelled forms of tourist - the 'reflective', 'unconcerned' and 'prosustainable' tourist.

Here we group individuals according to their environmental attitudes, to produce - in effect - a single categorical variable. This variable can be used to summarise and indicate how environmental attitudes cluster within a given population, (alongside the auxiliary socio-demographic characteristics of group members), as well as the relationships between attitude group membership and engagement in pro-environmental behaviours. Thus, whilst factor analysis highlights the composition of attitudinal inter-relationships at the individual level, segmentation highlights the distribution of attitudes within a population. This can be particularly valuable where there may be heteroscadicity along one or more underlying dimensions that might be produced by a factor analysis. With a construct as complex as environmental concern assuming homoscadicity with respect of its constituent variables or indeed of environmental behaviour variables that we might want to use it to predict is probably inadvisable and therefore exploring segmentation as an approach would appear justified.

In this research, we aim to answer the following questions:

- What groups exist in the UK population in respect of environmental attitudes?
- Do attitude-based groups vary by age, gender and socio-economic status (SES)?
- Is attitude group membership associated with pro-environmental behaviours?

Data for this analysis is taken from the 2009 wave of DEFRA's Survey of Public Attitudes and Behaviours towards the Environment, a large nationally represented study. Indicators of environmental attitudes are selected from the survey and are analysed using latent class analysis to produce a model that classifies participants by their attitudes towards the environment. These attitudes are then interpreted through the examination of within-class item probabilities. Following the interpretation of the classes of this model, between class variations in age, gender and socio- economic status are assessed. Finally, the association between environmental attitudes and level of pro-environmental behaviours are examined through regression analysis. We begin by locating the study within the wider context of the vexed nature of attitude-behaviour relationships, cluster-based studies of environmental attitudes and studies of associations between SES and environmental attitudes.

2. Background

2.1. **Environmental attitude-behaviour relationships**

Mounting scientific evidence suggests human-induced climate change may pose a significant threat to humans and the wider environment ('Fifth Assessment Report - Climate Change 2013'). In the 1970s, the revelation that environmental degradation is the consequence of 'maladaptive human behaviour' (Maloney and Ward 1973, 583) motivated social scientists to analyse individual motives underlying this behaviour. Such environmental studies concentrated primarily on environmental concern or attitudes as predictors of environmental behaviour. Often the measured attitudes have been ontologically broader in scope than the measured actions; for example, assessing how an individual cares about the environment and how this effects their recycling frequency (Rajecki 1990). What followed were largely inconsistent findings. Most attitudinal studies find that neither environmental concern nor attitudes correspond to behaviour (Tanner 1999). of the studies that did find associations between attitudes and behaviour, some found the effect sizes to be low to moderate (Hines, Hungerford, and Tomera 1987; Eckes and Six 1994).

Unsurprisingly, scepticism regarding the explanatory power of environmental concern ensued from this evidence and some scholars abandoned the claim that general environmental concern is a direct predictor of specific environmental behaviour at all. Instead, behaviour-specific attitudes have been tested as predictors of behaviour, adhering to the correspondence principle developed by (Ajzen and Fishbein 1980) which posits that only when the attitudinal and behavioural measures correspond to each other concerning the relevant action, context and time, is there a substantial relationship.

Focusing upon specific attitude-behaviour relationships, rather than general environmental concerns, has come at a cost. The reason the attitude concept received so much attention in psychology was in part due to its assumed function as predictor of multiple behaviours. Bamberg (2003) points out that specific attitudes do not fulfil this function, and can only predict the behaviour they are specific to; ontologically, attitudes towards recycling would appear to be *attitudes towards recycling behaviour* rather than attitudes towards the environment per se.

Diekmann and Preisendöerfer (1992) explain the lack of a consistent relationship between environmental attitudes and pro-environmental behaviour by using a low-cost/high-cost model. This model suggests that people choose to engage in pro-environmental behaviours that demand the least cost. 'Cost' is not only defined in an economic sense but also in a broader psychological sense that includes, among other factors, the time and effort needed to undertake a particular behaviour. Diekmann and Preisendöerfer (1992) suggest that environmental attitudes and low-cost pro-environmental behaviour (e.g. recycling) do correlate significantly and therefore, people who care about the environment tend to engage in activities such as recycling, but do not necessary engage in activities that are costlier and inconvenient such as driving less. Diekmann and Preisendöerfer (1992) conclude that positive environmental attitudes can directly influence easy, low-cost pro-environmental behaviour such as recycling, but that people with high levels of environmental awareness might not be willing to make bigger lifestyle sacrifices. Though, it is important to note that what an individual perceives as a low-cost pro-environmental behaviour is partially dependant on their personal circumstances. Therefore, other factors (aside from the attitude and the behaviour) are in play too and therefore should to be considered when examining this attitude-behaviour relationship.

Other work supports this intuitively-plausible conclusion. For example, in a study of Whitmarsh (2009) found recycling to be the most common mitigating response to environmental concern, alongside resistance to changing travel habits based on findings from a UK sample. When provided with a list of alternative mitigation strategies, the majority of the study sample claimed that they would recycle household waste and improve home energy efficiency. Whitmarsh also found that car owners held negative views of public transport and were highly unlikely to increased their usage of public transport over driving. This is in line with other studies who find that few would change their transport habits for more environmentally friendly ones (Bord, O'Connor, and Fisher 2000; Fortner et al. 2000; O'Connor et al. 2002). Overall, Whitmarsh found environmental concern more often motivates recycling and domestic conservation than transport-related conservation.

2.2. **Clustering by environmental attitudes**

In the UK, Barr et al. (2006) examined how pro-environmental behaviours were practiced on a daily basis and how such practices varied according to lifestyle. Data were collected from 1265 participants residing in Devon (a UK county), capturing environmental knowledge, attitudes and behaviour. Individuals were grouped into distinctive segments according to their level of pro-environmental attitudes and behavioural commitment using cluster analysis. Barr et al. identified four distinct groups of people defined by their behaviour patterns and attitudes: (a) committed environmentalists, (b) mainstream environmentalists, (c) occasional environmentalists, and (d) non-environmentalists. Additional qualitative data were then collected from eight focus group discussions based on the quantitative findings. Thus a mixture of quantitative and qualitative analysis is used to segment the population. The study's geographical focus means that the findings are pertinent to that area only and should only be generalised - even to the rest of the UK - with caution. We also note that Barr et al's categories effectively form an ordinal variable. Arguably factor analysis is a more appropriate technique in such a situation as the compositional flexibility of LCA (its main data analytical advantage over factor analysis) is effectively not utilised with such data/results. This outcome is not replicated in other studies using segmentation including our own, so the problem (such as it is a problem) is not general.

Subsequently, DEFRA (2008) produced a UK-wide environmental typology based on self-reported pro-environmental behaviours using data taken from their 2007 Environmental Attitudes and Behaviours Survey. This segmentation was intended to be used to understand and promote 'green' or pro-environmental behaviours and was widely reported in the media. Unfortunately, little information is given on the methods used in the study. It is likely that the methods used are similar to Barr et al. (2006) (i.e. cluster analysis as well as qualitative research to contextualise the results), but the paucity of methodological detail is concerning. This study produced a model consisting of seven clusters: (1) positive green; (2) waste watchers; (3) concerned consumers; (4) side-line supporters; (5) cautious participants; (6) stalled starters; and (7) honestly *Disengaged*. DEFRA claim that this model contributes to an understanding of how environmental attitudes, values, current behaviours and motivations and barriers are packed together for defined segments of the population. Both the Barr et al. (2006) and DEFRA (2008) studies also combine measures of broad-level environmental concern and behavioural measures in the same model, conflating the two concepts.

Unlike Barr et al. (2006) and DEFRA (2008), Maibach et al. (2011) produced an environmental attitude typology using attitudinal measures only, acquired from a nationally representative sample. Results of such analysis are therefore also representative, in addition to being conceptually more straightforward. Maibach et al. conducted this analysis with the intention that it could be used to improve the efficacy of public engagement campaigns. The study assessed belief in climate change and support for environmental policies among a nationally representative survey of American adults (N = 2164). The sample was segmented according to homogenous item response patterns using LCA, producing six segments. These six classes can broadly be divided into three groups of pro-, neutral- and anti-environmental perceptions, structured in terms of an ordinal variable. The primary distinction between the two negative environmental classes – the Doubtful and the Dismissive classes – is the belief in the human contribution to climate change. The Dismissive class denies the existence of climate entirely, whereas most the Doubtful class believes that climate change is a natural phenomenon.

Sibley and Kurz (2013) examined this distinction among climate change sceptics. Based on data from New Zealand, the authors used LCA to cluster people according to their views on climate change. They hypothesised that a distinction exists between those who are sceptical of climate change itself and those who are sceptical of human action as a driver of climate change, and that these attitudes would have differing associations with pro-environmental behaviour. Sibley and Kurz (2013) produced a four-class model consisting of (a) Climate Believers, (b) Undecided/Neutral, (c) Climate Skeptics, and (d) Anthropogenic Climate Skeptics, supporting their hypothesis of two distinct forms of climate change scepticism. It was also found that belief in the reality of climate change was significantly more predictive of pro-environmental behaviour and policy support than belief in the human involvement in climate change. From this, the authors concluded that it more important to convince people of the existence of climate change rather than its causes or the level of human involvement.

2.3. Environmental attitudes and socio-economic status

Van Liere and Dunlap (1980) proposed that environmental concern is positively associated with both level of education and income. Though, empirical evidence for these hypotheses is mixed. Some studies suggest that high-income and well-educated people are more likely to have post-materialist views emphasising quality of life and indeed environmental sustainability instead of economic growth and material possessions (Inglehart 1995; Liere and Dunlap 1980). On the other hand Dietz et al. (1998) and Kanagy et al. (1994) found income and occupation to be weak predictors of EC. However, level of education was found to be moderately associated with EC, with the well-educated displaying more concern about environmental problems than their less-educated counterparts.

DEFRA (2008) is the only study of those reviewed here that has examined the social characteristics of environmental attitude class membership, despite the wealth of evidence suggesting that environmental attitudes are heavily influenced by social, economic and demographic factors (Black, Collins, and Snell 2001; Exley and Christie 2002; Steg, Geurs, and Ras 2001). Unfortunately, DEFRA (2008) did not disclose the details of their methods and consequently have produced uninformative segmentation models, with the analytic detail behind these now lost (pers. comm.). Furthermore, variables relating to engagement with the natural environment appear to have been included in the model with no real consideration for what they represent – whether attitude, knowledge, behaviour or intention. It is unclear, therefore, what exactly has been captured by the clusters, despite being based on a nationally representative precursor to that used in the present study.

In order to develop more meaningful clusters, it is necessary to make explicit one's assumptions regarding the relationship of attitudes to behaviours. As highlighted by Pendergraft (1998), using theory to dictate class membership (rather than allowing it to be determined empirically) can be problematic. Strict application of a theoretical framework forces respondents to fit a pre-conceived notion of how they should be categorised rather than allowing categories to reflect the data. A more moderate methodological position is that theoretical frameworks are used to inform the interpretation, but not to the point where they impede alternative substantive conclusions. Hence in this case our thinking is informed by our knowledge of the environmental attitude/behaviour literature as described above, but we deliberately permit the classes to be significantly guided by the data.

We examine the environmental attitude-behaviour relationship by grouping participants according to homogenous environmental attitudes. We further examine the associations between group membership and both SES and pro-environmental behaviours. The number of groups are dictated by model fit, rather than theory, and an ontological distinction is maintained between environmental attitudes and behaviours throughout the analysis of this study.

3. Data and Methods

Data for this analysis is taken from DEFRA's 2009 Survey of Public Attitudes and Behaviours towards the Environment (EAS). This dataset is explicitly divided into three sections: Environmental Attitudes, Environmental Behaviours, and Household and Respondent Characteristics.

3.1. **Measures of environmental attitudes**

Variables for our analysis were selected from the 25 measures contained within this latter section. These were developed by DEFRA to measure British public attitudes towards the environment, without commitment to one specific theoretical framework. Each measure consists of a statement, to which the participant indicates his/her level of agreement on a 5-point Likert scale (strongly agree – strongly disagree).

Nine measures of environmental attitudes were selected from the dataset for this analysis, these selected variable capture attitudes to the natural environment generally and ascribe to our theoretical assumption that EC is primarily a cognitive and affective state, as described above (see Table 1). Variables were not included in our analysis if they only captured attitudes towards specific environmental behaviours (as our aim is to capture attitudes to the natural environment not actions impacting the environment) or ask about the financial penalties of conducting environmental behaviour (participant wealth my act as a confounder when examining the association between these attitudes and environmental behaviour).

Environmental attitude statements that were in part behavioural – that is, statements that commented on the execution, frequency or opinion of environmental behaviour – were excluded, in order to maintain an ontological divide between attitude and behaviour. Therefore, statements which asked for attitude towards environmental behaviour such as 'I make an effort to buy things from local retailers and suppliers' and 'I would only travel by bus if I had no other choice' were excluded from our analysis.

Furthermore, statements that remarked on the willingness of participants to incur a financial penalty for engaging in environmentally detrimental activities or pay an increased price for comparatively environmentally friendly products were also excluded. Responses to such statements are indicative of participant willingness to dispense with monetary resources to achieve a positive effect (or avoid a negative effect) on the environment; consequently, responses are potentially influenced by participant income or wealth (and indeed their attitudes to the same). Therefore, statements such as ‘People who fly should bear the cost of the environmental damage that air travel causes’ and ‘I would be prepared to pay more for environmentally-friendly products’ were excluded. Including such variables in our analysis would likely introduce additional variance into the analysis – constraining EC and potentially producing results relating to income or wealth. Undoubtedly, such variables do have a relationship with environmental concern, but they are likely to be confounded.

3.2. Measures of environmental behaviour

Participants of the EAS were asked questions relating to their pro-environmental behaviours across four behaviour categories: recycling, travel, food and household (categories were defined by DEFRA). Measures capturing whether participants have adopted pro-environmental behaviours relating to these categories (such as recycling more or reducing energy consumption in the home) were used in our analysis.

DEFRA’s ‘standard’ scale or ‘repeat purchasing’ response scales were used for these variables. These scales are nominal and complex, with reasons for not conducting these behaviours or feedback following the behaviour if conducted were incorporated into the response categories, making results difficult to interpret. As such, measures captured by these DEFRA scales have been dichotomised to reflect whether the participant simply is or isn’t engaging in the behaviour in question (shown in Table 2 and Table 3). This dichotomisation was such that, response categories prefixed with the statement ‘I am already doing this’ or ‘I’ve done this’ were coded as 1, and responses indicating that the action has not been taken (i.e. ‘I haven’t heard of this’ or ‘I am thinking of doing this’) were coded as 0.

Some behavioural measures were restricted to only a small proportion of the population. This included behaviours that were conditional on wealth or property ownership, such as the installation of solar panels and home insulation. To avoid introducing bias against low-income respondents and the exclusion of a large portion of respondents, these items were excluded. Table 4 shows the behavioural measures used for analysis in this study and indicates which have been dichotomised.

3.3. Measures of socio-economic status

Measures of educational attainment, combined household income and social grade are used to examine inter-class variations in SES. Social grade is captured using the NRS (National Readership Survey) social grades system (“Social Grade | National Readership Survey” 2016). This measure is based on the occupation of either the individual being interviewed, or head of the household. Classification is divided into managerial or professional roles, junior or clerical roles, skilled manual workers and unskilled manual workers. The lowest social grade refers to non-workers such as pensioners or those seeking employment.

3.4. Latent Class Analysis

LCA is a statistical method for identifying latent classes based on a set of observed response items (Hagenaars, J.A.P. and McCutcheon, A.L. 2002). Latent classes are unobserved groups containing individuals who are homogeneous in terms of particular criteria. Formally, latent classes are represented by categories of a nominal latent variable. LCA estimates conditional class membership probability (and assigns individuals to their most likely class based on this conditional probability) and item response probability. The conditional membership probability represents the probability that an individual belongs to a latent class, conditional on their answers to the indicators (Henry and Muthén 2010). Item response probability is the probability that class members will give response x to an indicator y.

This decision to use LCA over cluster analysis was made based on the superiority of LCA as a clustering method. LCA is model based, and as such, conclusions from the chosen model can be generalised to the population from which the sample was drawn (in this case, the UK population). LCA also imposes the assumption that data are generated by a mixture of underlying probability distributions (Vermunt, J.K. et al. 2004). Therefore, based on the statistical concept of likelihood, participants are not only assigned to classes, but also have a probability class membership for all classes. Another advantage of LCA is that it does not require decisions to be made about the scaling or transformations of the observed variables. For example, when working with normal distributions with unknown variances, results will be the same irrespective of whether the variables are normalised. LCA is unaltered by linear transformations on variables, so standardisation is unnecessary (Francis 2006). This is very different to standard non-hierarchical cluster methods like K-means, where scaling is often an issue. LCA also provides diagnostics, such as the Bayesian information criterion (BIC), to determine the optimal number of classes. Determining the number of clusters for a cluster analysis model is less sophisticated and often relies on the (subjective) interpretation of a dendogram or somewhat arbitrary statistics such as the VRC criterion.

The analysis in this paper does not use an a priori hypothesis to dictate the number or nature of latent classes for EC. Therefore, several models are generated, differentiated by the number of latent classes. The resulting fit indexes is compared to determine which model best corresponds to the observed data (Finch and Bronk 2011).

LCA regression analysis is performed in this paper using a two-step approach where latent class membership is exported and used as a predictor or explanatory variable in subsequent regression analysis. We acknowledge that this approach has its limitations, however, performing LCA regression in a single step (or even in the recently proposed three-step approach, see (Asparouhov and Muthén 2014) severely alters latent class formation (Asparouhov and Muthén 2014; Asparouhov and Muthén 2015), thus doing so would invalidate our results.

Latent class analysis was performed in Mplus (version 7) while regression analysis and descriptive statistics were conducted using Stata 14.

4. Analysis and results

4.1. What groups of environmental attitudes exist in the UK?

The selected measures of environmental attitudes (displayed in Table 1) are analysed using latent class analysis; grouping participants into classes defined by homogeneity of environmental attitudes. To determine the optimal number of latent classes, goodness of fit statistics are examined for two- to six-class models (Table 5). The results suggest both a two-class and a four-class model fit the data, as indicated by the adjusted Lo-Mendell-Ruben (ALMR) p-value (indicating that the mixture model with k classes fits the data better than the simpler k-1 class model.) and high entropy. Furthermore, inflections can be observed in both information criterion and log likelihood for the two and four-class models as shown in Figure 1, suggesting these either of these models are viable options. The four-class model was chosen for this analysis as item probabilities for the two-class model suggest that this model is overly simplistic; only demonstrating that some individuals express a high level of EC, while others slightly less so. It is likely that this two-class model has grouped together smaller classes, obscuring potentially valuable subgroups. This is common in binary class models (as highlighted by Pendergraft, 1998). Item probabilities from the four-class model are displayed in Figure 2, revealing distinct and interesting subgroups that were not revealed in the two-class model. We take the view that this four-class model offers more potential for insight than the two-class model and hence is most suitable for present purposes.

4.2. Environmental attitude groups

We interpret the environmental attitude groups as follows. Class 1 members have the overall highest probability of agreeing with positive statements and lowest probability of agreeing with negative statements (as shown in Figure 2). This class has been accordingly labelled as *Pro-environment*. Class 2 members show a similar pattern, but with less extreme item probabilities for positive and negative statements. Given this, as well as Class 2 having the highest proportion of participants, we label it the *Neutral Majority*.

Class 3 members exhibit a paradoxical combination of item probabilities, with similar scores for both positive and negative statements (as shown in figure 2). Item probabilities do not decrease for negative statements, nor increase for positive statements (as they do for classes 1 and 2). Instead, probabilities are between 0.4 and 0.7 for all nine items. Such item probabilities suggest that members of this class are moderately likely to agree that an environmental crisis has been exaggerated, that it is a low priority and too far in the future to be of concern. On the other hand, these class members also appear to be moderately likely to be concerned about the countryside and animal species, the planet's ability to sustain an ever-growing human population, and acknowledge that if trends continue there will be a major environmental disaster. This combination of views is not only complex but also contradictory. This attitude cluster could reflect a form of denial, where environmental problems are recognised but then dismissed and trivialised as a coping mechanism. Given these contradictory item probabilities, this class has been labelled as *Paradoxical*. It is theoretically possible that this group is an artefactual group driven by satisficing bias. However, systematic sensitivity analyses of other questions in the survey indicated that the group was actually slightly less likely than the others to give responses patterns consistent with satisficing and so we believe that this was not the driver for the response pattern found in the group.

It is possible that the paradoxical group could hold contradictory positions simply because environmental issues are not particularly salient to their thinking or something they feel intensely about. Another possibility is that people in the paradoxical category give different weight to different types of environmental issues, with those such as animal protection and overpopulation being given more weight. This might reflect the way in which some environmental issues can perceived as spatially and temporally remote (L. E. Whitmarsh et al. 2011). Perhaps, also, people in this group agree with the proposition that that if trends continue there will be a major environmental disaster simply through the extension of the logic. Or perhaps they are not sure what they think and they have labile attitudes and beliefs in these areas. These are all speculations based on inductive findings, but are intriguing nevertheless and arguably warrant further research.

Class 4 members have the lowest probability for positive items (as shown in Figure 2). Probability for negative items is also low, although not as low as *Neutral Majority* and *Pro-environment* classes. While the low probability for positive items is indicative of scepticism or denial, item probability for negative items is too low to support this interpretation. Given the low item probability for all items, it is likely that class members are *Disengaged* or apathetic towards environmental issues. This class has been labelled "*Disengaged*". Class probabilities and sizes are shown in Table 6.

This class structure does indicate that there is an underlying linear construct of environmental concern but that there is a diversity of response patterns at the not concerned end of the scale; this is shown schematically in Figure 3:

4.3 **How do attitude group members vary by age, gender and SES?**

Multinomial regression analysis is conducted to determine how class members vary by age, gender and SES where these sociodemographic measures were regressed onto a four-category measure of class membership. For this regression analysis, the Neutral Majority class was used as the reference category as this is the largest category and the most neutral. As shown in Table 7, age, gender and the three measures of SES used in this study are all significantly associated with attitude class membership. These results show that most men and women belong to the *Pro-environment* and *Neutral Majority* classes. Across all age groups, the highest proportion of Disengaged (25%) exists in the 60+ age band. In contrast, the highest proportion of Paradoxicals (27%) exists in the 16-24 age band, higher than the proportion of Pro-environmentals in this age band (this does not occur for any other age category). The top social grade (managerial or professional roles) has the highest proportion of Pro-environmentals (44%) compared to other social grades. Across all social grades, the Disengaged and Paradoxical classes have their highest proportions in the two lowest social grades.

4.4 **How is group membership associated with pro-environmental behaviours?**

The association between environmental class membership and the specific measure of environmental behaviour are each assessed individually using binary logistic regression. The *Disengaged* class is used as the reference category for this analysis as the response patterns of these class members suggest that they are the least interested in environmental issues compared to the other classes, we therefore want to determine how other, stronger or more complicated response patterns are associated with behaviours in comparison to this *Disengaged* group. Class membership is regressed onto 16 measures of pro-environmental behaviours separately, controlling for age and gender.

Table 8 indicates that the odds of engaging in environmental behaviour are higher among *Pro-environment* class members. *Pro-environment* class membership is a significant predictor of all but one measures of behaviour and Membership of the *Neutral Majority* class is positively associated with the majority of behaviour (12/16). Though of these significant relationships, odds ratios are smaller than those obtained from the *Pro-environment* class. This provides further evidence that greater environmental concern leads to a higher probability of engaging in pro-environmental behaviour. *Paradoxical* class membership is only significantly associated with two measures of behaviour. Membership of this class is significantly associated with reducing water usage in the home and buying fresh local produce (compared to membership of the *Disengaged* class). Nonetheless, the odds of *Paradoxical* class members engaging in these behaviours are lower than for members of the *Pro-environment* and the *Neutral Majority* classes. The majority of measures in this table have a high f ratio, indicating that the attitudinal groups are distinct classes that capture a large proportion of the variance in the likelihood of pro-environmental behaviour.

5. Discussion

Our study has grouped respondents according to homogenous response patterns using LCA, identifying four categories of concern for the environment: *Pro-environment*, *Neutral Majority, Disengaged* and *Paradoxical*. Participant item response probabilities inform the initial interpretation and titles for the classes.

The *Pro-environmentals* are named as such because they have the highest probabilities for agreeing with pro-environmental statements. Item probabilities for the *Neutral Majority* group suggest that members possess a positive cognitive evaluation of the environment, though it is weak in strength. The *Disengaged* have the lowest probability of agreeing with pro-environmental statements and the second highest probability of agreeing with the negative-environmental statements. The pattern of responses of the *Paradoxical* is apparently self–contradictory. The respondents have, on average, a very high average score for denial, suggesting that their ‘odd’ responses to statements may be as a result of an inability or unwillingness to consider or accept information on climate change. A large proportion of this class do not accept that climate change is due to energy consumption, making them similar to the doubtful group found by Maibach et al. (2011) and distinguishing them from the *Disengaged* class, which has the highest proportion of older participants, low-income and low social-grade workers and a higher proportion of men than the *paradoxical* class.

Our analysis of the socio-demographic profile of class members has found that both *Pro-environmental* and *Neutral Majority* groups consist largely of middle aged, middle class, well-educated individuals. The *Disengaged* are primarily young respondents (age <30) from the middle and lower social grades. These classes have the lowest levels of education, with most members not educated past GCSE (secondary school) level (albeit with the latter being a co-correlate of class members’ age). This finding that different age groups have different compositions of attitude class membership suggests that age may affect how an individual understands/copes with environmental change.

In our examination of the associations between latent class membership and pro-environmental behaviours, we find that both *Neutral Majority* and *Pro-environment* class membership is positively associated with the majority of behavioural measures (though the latter group more so). *Paradoxical* class membership is only significantly associated with two measures of behaviour. *Pro-environment* class members are less satisfied with the level of behaviour that they engage in, despite their comparatively higher levels of pro-environmental behaviour. The *Disengaged* and the *Paradoxical* classes report the lowest levels of behaviour but the highest level of satisfaction. In short, the more people do for the environment, the less satisfied they are with what they do, though we are not - here - attributing any direct causality between these two attributes. The dissatisfaction felt amongst members of the *Pro-environmental* group could potentially be because they recognize that their own behaviours have a very modest impact, given the size of the climate change problem. In contrast, the satisfaction of the *Paradoxical* and *Disengaged* reflects their shared lack of real recognition and engagement with the problem.

Pro-environment class membership is found to be a significant predictor of taking fewer flights, as well as walking and using public transportation over driving. Membership of the *Neutral Majority* class is only a significant predictor of taking fewer flights, and using public transport, while *Paradoxical* class membership does not predict any measures pro-environmental travel behaviour. On the surface at least, these findings contradict previous research conducted by Whitmarsh (2009) and Diekmann and Preisendöerfer (1992), who found that actual transport behaviours are not affected by attitudes towards the environment. Whitmarsh (2009) proposed that travel behaviours are driven by habit, and difficult to alter, making them high-cost behaviours. Diekmann and Preisendöerfer (1992) also suggested that environmental attitudes are only able to influence low-cost behaviours such as recycling, because they are easy to do in terms of time, effort and financial cost. As such, previous research suggests that pro-environmental attitudes per se are not strong enough to drive high-cost behaviour, in this case, a substantial change in one's use of transportation. Yet in contrast, the results presented here do suggest that concern is enough to motivate such high-cost behaviour, with the exception of driving in a fuel-efficient way.

Through use of LCA and grouping participants according to homogenous response patterns, we have been able to find a significant and substantial ability of our attitude classes to predict environmental behaviour, adding substantially to previous studies (Donald E. Blake 2001; Stuart P. Cottrell 2003; Catherine Mobley, Wade M. Vagias, and Sarah L. DeWard 2010). Our analysis expands upon the existing DEFRA segmentation studies by focusing on environmental concern (EC) and social characteristics in terms of class membership. It differs from previous studies of UK, national-level environmental attitudes by treating EC as categorical and by using latent class analysis to divide EC variance into categories. More generally, the study therefore emphasises the *distribution* of participant response patterns, rather than the structural relationships between responses. While previous studies have commonly adopted factor analysis as their primary method of analysis, we argue that when seeking to understand the distribution of environmental concern amongst a given population, this may not be best captured by multiple, linear, correlated structures. The method is therefore beneficial to population level studies in the field of environmental studies, allowing researchers to categorise populations according to their homogenous response patterns. Our choice of method parallels the increasing use of LCA in marketing, tourism studies and other fields where population segmentation is useful (López-Sánchez and Pulido-Fernández, 2016).

Limitations of this paper include the use of cross-sectional data which prohibits use from fully understanding the causal nature of the attitudes and behaviours examined in this study. We are also bound by the limitations of the available data and thus only able to examine a small selection of environmental behaviours. Finally, it is important to note that DEFRA's behavioural data is not observed but reported: that a respondent has said that they are already taking a specific pro-environmental action tells us nothing about the extent to which they practice this or abstain from an action.

6. Conclusion

We have applied latent class analysis to understand environmental concern as inferred from a large, government-commissioned national UK dataset on environmental behaviour and attitudes. Whereas factor analysis is more commonly used to study the relationships between such variables, here our choice of methodology is driven by the objective of understanding the distribution of environmental concern across the UK population.

Among our findings, two are particularly notable. First, our results contradict most previous research, with the environmental attitude classes being highly predictive of environmental behaviour. It is not clear how this should be interpreted, but one area for further attention may be question phrasing and any differences in this respect between the DEFRA questionnaire and other studies. Secondly, we identify a *Paradoxical* group who view talk of environmental crisis as exaggeration, but who at the same time are concerned about specific environmental issues and agree that current environmental trends will be problematic if they continue. This, too, raises questions and potentially implications for environmental communication or messaging. The *Paradoxicals* are a numerically non-negligible group of some 16% of the adult population and it appears that they might be amenable to pro-environmental mobilisation if their concerns were better understood. Overall, we have found use of LCA to have raised interesting issues in what is still the UK's largest dataset of environmental behaviour and attitudes. Further research is needed to establish whether the findings from this study can be replicated, and how class membership changes over time through age, period or cohort effects.

5 Bibliography

Ajzen, I, and M Fishbein. 1980. *Understanding Attitudes and Predicting Social Behaviour*. Prentice-Hall.

Asparouhov, Tihomir, and Bengt Muthén. 2014. "Auxiliary Variables in Mixture Modeling: Three-Step Approaches Using Mplus." *Structural Equation Modeling: A Multidisciplinary Journal* 21 (3): 329–41. doi:10.1080/10705511.2014.915181.

———. 2015. "Auxiliary Variables in Mixture Modeling: Using the BCH Method in Mplus to Estimate a Distal Outcome Model and an Arbitrary Secondary Model." *Mplus Web Notes: No. 21*, May. https://www.statmodel.com/examples/webnotes/webnote21.pdf.

Bamberg, Sebastian, and Peter Schmidt. 2003. "Incentives, Morality, Or Habit? Predicting Students' Car Use for University Routes With the Models of Ajzen, Schwartz, and Triandis." *Environment and Behavior* 35 (2): 264–85. doi:10.1177/0013916502250134.

Barr, Stewart, and Andrew Gilg. 2006. "Sustainable Lifestyles: Framing Environmental Action in and around the Home." *Geoforum* 37 (6): 906–20. doi:10.1016/j.geoforum.2006.05.002.

Black, Colin, Alan Collins, and Martin Snell. 2001. "Encouraging Walking: The Case of Journey-to-School Trips in Compact Urban Areas." *Urban Studies* 38 (7): 1121–41. doi:10.1080/00420980124102.

Bord, Richard J., Robert E. O'Connor, and Ann Fisher. 2000. "In What Sense Does the Public Need to Understand Global Climate Change?" *Public Understanding of Science* 9 (3): 205–18. doi:10.1088/0963-6625/9/3/301.

Catherine Mobley, Wade M. Vagias, and Sarah L. DeWard. 2010. "Exploring Additional Determinants of Environmentally Responsible Behavior: The Influence of Environmental Literature and Environmental Attitudes." *Environment and Behavior* 42 (4): 420–47. doi:10.1177/0013916508325002.

DEFRA. 2008. "A Framework for Pro-Environmental Behaviours." HMSO, London.

Diekmann, Andreas, and Peter Preisendörfer. 1992. "Persónliches umweltverhalten: Diskrepanzen zwischen Anspruch und Wirklichkeit. [Ecology in everyday life: Inconsistencies between environmental attitudes and behavior.]." *Kölner Zeitschrift für Soziologie und Sozialpsychologie* 44 (2): 226–51.

Dietz, Thomas, Paul C. Stern, and Gregory A. Guagnano. 1998. "Social Structural and Social Psychological Bases of Environmental Concern." *Environment and Behavior* 30 (4): 450–71. doi:10.1177/001391659803000402.

Donald E. Blake. 2001. "Contextual Effects on Environmental Attitudes and Behavior." *Environment and Behavior* 33 (5): 708–25. doi:10.1177/00139160121973205.

Eckes, T., and B. Six. 1994. "Fakten Und Fiktionen in Der Einstellungs-Verhaltens-Forschung: Eine Meta-Analyse." *Zeitschrift Für Sozialpsychologie* 25 (4): 253–71.

Ehrlich, Oren, Xiang Bi, Tatiana Borisova, and Sherry Larkin. 2016. "A Latent Class Analysis of Public Attitudes toward Water Resources with Implications for Recreational Demand." https://ideas.repec.org/p/ags/aaea16/235853.html.

Exley, Sonia, and Ian Christie. 2002. "Off the Buses." In *British Social Attitudes: The 19th Report*, edited by A. Park, J. Curtice, K. Thomson, L. Jarvis, and C. Bromley, 1–26. London: SAGE Publications Ltd. http://eprints.ioe.ac.uk/2453/.

"Fifth Assessment Report - Climate Change 2013." n.d. http://www.ipcc.ch/report/ar5/wg1/.

Finch, W. Holmes, and Kendall Cotton Bronk. 2011. "Conducting Confirmatory Latent Class Analysis Using Mplus." *Structural Equation Modeling: A Multidisciplinary Journal* 18 (1): 132–51. doi:10.1080/10705511.2011.532732.

Fortner, Rosanne W., Jae-Young Lee, Jeffrey R. Corney, Samantha Romanello, Joseph Bonnell, Brian Luthy, Claudia Figuerido, and Nyathi Ntsiko. 2000. “Public Understanding of Climate Change: Certainty and Willingness to Act.” *Environmental Education Research* 6 (2): 127–41. doi:10.1080/713664673.

Francis, B. 2006. “What Is Latent Class Analysis?” Conference presented at the ESRC Research Methods Festival 2006, St Catherine College, Oxford. http://www.ccsr.ac.uk/methods/festival/.

Hagenaars, J.A.P., and McCutcheon, A.L. 2002. *Applied Latent Class Analysis*. Cambridge University Press. https://pure.uvt.nl/portal/en/publications/applied-latent-class-analysis(04ed67ad-e3b5-439f-bf07-3211e1203288).html.

Henry, Kimberly L., and Bengt Muthén. 2010. “Multilevel Latent Class Analysis: An Application of Adolescent Smoking Typologies with Individual and Contextual Predictors.” *Structural Equation Modeling : A Multidisciplinary Journal* 17 (2): 193–215. doi:10.1080/10705511003659342.

Hines, Jody M., Harold R. Hungerford, and Audrey N. Tomera. 1987. “Analysis and Synthesis of Research on Responsible Environmental Behavior: A Meta-Analysis.” *The Journal of Environmental Education* 18 (2): 1–8. doi:10.1080/00958964.1987.9943482.

Inglehart, Ronald. 1995. “Public Support for Environmental Protection: Objective Problems and Subjective Values in 43 Societies.” *PS: Political Science & Politics* 28 (1): 57–72. doi:10.2307/420583.

Kanagy, Conrad L., Craig R. Humphrey, and Glenn Firebaugh. 1994. “Surging Environmentalism: Changing Public Opinion or Changing Publics?” *Social Science Quarterly* 75 (4): 804–19.

Liere, Kent D. Van, and Riley E. Dunlap. 1980. “The Social Bases of Environmental Concern: A Review of Hypotheses, Explanations and Empirical Evidence.” *Public Opinion Quarterly* 44 (2): 181–97. doi:10.1086/268583.

López-Sánchez, Y., and J. I. Pulido-Fernández. 2016. “In Search of the pro-Sustainable Tourist: A Segmentation Based on the Tourist ‘sustainable Intelligence’.” *Tourism Management Perspectives* 17: 59–71.

Maibach, Edward W., Anthony Leiserowitz, Connie Roser-Renouf, and C. K. Mertz. 2011. “Identifying Like-Minded Audiences for Global Warming Public Engagement Campaigns: An Audience Segmentation Analysis and Tool Development.” *PLOS ONE* 6 (3): e17571. doi:10.1371/journal.pone.0017571.

Maloney, Michael P., and Michael P. Ward. 1973. “Ecology: Let’s Hear from the People: An Objective Scale for the Measurement of Ecological Attitudes and Knowledge.” *American Psychologist* 28 (7): 583–86. doi:10.1037/h0034936.

Nylund, Karen, Amy Bellmore, Adrienne Nishina, and Sandra Graham. 2007. “Subtypes, Severity, and Structural Stability of Peer Victimization: What Does Latent Class Analysis Say?” *Child Development* 78 (6): 1706–22. doi:10.1111/j.1467-8624.2007.01097.x.

O’Connor, Robert E., Richard J. Bord, Brent Yarnal, and Nancy Wiefek. 2002. “Who Wants to Reduce Greenhouse Gas Emissions?” *Social Science Quarterly* 83 (1): 1–17. doi:10.1111/1540-6237.00067.

Rajecki, D. W. 1990. *Attitudes, 2nd Ed.* Sinauer Associates. http://psycnet.apa.org/index.cfm?fa=search.displayRecord&uid=1990-97710-000.

Sibley, Chris G., and Tim Kurz. 2013. “A Model of Climate Belief Profiles: How Much Does It Matter If People Question Human Causation?” *Analyses of Social Issues and Public Policy* 13 (1): 245–61. doi:10.1111/asap.12008.

“Social Grade | National Readership Survey.” 2016. Accessed November 3. http://www.nrs.co.uk/nrs-print/lifestyle-and-classification-data/social-grade/.

Steg, Linda, Karst Geurs, and Michiel Ras. 2001. “The Effects of Motivational Factors on Car Use: A Multidisciplinary Modelling Approach.” *Transportation Research Part A: Policy and Practice* 35 (9): 789–806. doi:10.1016/S0965-8564(00)00017-3.

Steiner, B. E., A. O. Peschel, and C. Grebitus. 2017. “Multi-Product Category Choices Labeled for Ecological Footprints: Exploring Psychographics and Evolved Psychological Biases for Characterizing Latent Consumer Classes.” *Ecological Economics* 140 (C): 251–64.

Stuart P. Cottrell. 2003. “Influence of Sociodemographics and Environmental Attitudes on General Responsible Environmental Behavior among Recreational Boaters.” *Environment and Behavior* 35 (3): 347–75. doi:10.1177/0013916503035003003.

TANNER, CARMEN. 1999. “CONSTRAINTS ON ENVIRONMENTAL BEHAVIOUR.” *Journal of Environmental Psychology* 19 (2): 145–57. doi:10.1006/jevp.1999.0121.

Van Gaalen, Ruben I., and Pearl A. Dykstra. 2006. “Solidarity and Conflict Between Adult Children and Parents: A Latent Class Analysis.” *Journal of Marriage and Family* 68 (4): 947–60. doi:10.1111/j.1741-3737.2006.00306.x.

Vermunt, J.K., Magidson, J., Lewis-Beck, M., Bryman, A., Liao, T.F., and Department of Methodology and Statistics. 2004. “Latent Class Analysis.” In *The Sage Encyclopedia of Social Sciences Research Methods*, 549–53. Sage. https://pure.uvt.nl/portal/en/publications/latent-class-analysis(0caedd00-27c1-42bd-bb4e-d1dcb0864956).html.

Whitmarsh, Lorraine. 2009. “Behavioural Responses to Climate Change: Asymmetry of Intentions and Impacts.” *Journal of Environmental Psychology* 29 (1): 13–23. doi:10.1016/j.jenvp.2008.05.003.

Whitmarsh, Lorraine E., Paul Upham, Wouter Poortinga, Carly McLachlan, Andrew Darnton, Fionnguala Sherry-Brennan, Patrick Devine-Wright, and Christina C. Demski. 2011. “Public Attitudes, Understanding, and Engagement in Relation to Low-Carbon Energy. A Selective Review of Academic and Non-Academic Literatures : Report for RCUK Energy Programme.” http://www.rcuk.ac.uk/RCUK-prod/assets/documents/energy/EnergySynthesisFINAL20110124.pdf.

6 Appendix

6.3 Tables

Table 1: Measures of environmental attitudes used in this analysis

Variable Name	Statement
Major Disaster	*If things continue on their current course, we will soon experience a major environmental disaster.*
Limited Resources	*The Earth has very limited room and resources.*
Crisis Exaggerated	*The so-called 'environmental crisis' facing humanity has been greatly exaggerated.*
Too Far in Future	*The effects of climate change are too far in the future to really worry me.*
Over Populated	*We are close to the limit of the number of people the earth can support.*
Changes to Countryside	*I do worry about the changes to the countryside in the UK and the loss of native animal and plants.*
Loss of Animal Species	*I do worry about the loss of animal species and plants in the world.*
Beyond Control	*Climate change is beyond control – it's too late to do anything about it.*
Low Priority	*The environment is a low priority compared to other things in my life.*

Table 2: Dichotomous recode of the DEFRA ‘Standard’ scale

DEFRA ‘Standard’ scale	Dichotomous Recode
I haven’t heard of this	I am not doing this
I don’t really want to do this	
I haven’t really thought about doing this	
I’ve thought about doing this, but probably won’t do it	
I’m thinking about doing this	
I’ve tried doing this, but I’ve given up	
I’m already doing this, but I probably won’t manage to keep it up	I am already doing this
I'm already doing this and intend to keep it up	

Table 3: Dichotomous recode of the ‘Regular Purchasing’ scale

DEFRA ‘Regular Purchasing’ scale	Dichotomous Recode
I haven’t heard of this	I haven’t done this
I don’t really want to do this	
I haven’t really thought about doing this	
I’ve thought about doing this, but probably won’t do it	
I’m thinking about doing this	
I’ve tried doing this, but I’ve given up	
I’ve done this, but I probably won’t do it again	I have done this
I’ve done this and intend to do it again	

Table 4: Measures of specific pro-environmental behaviours used in this analysis

Category	Measure of behaviour
Recycling	Recycling items rather than throwing them away
	Reuse items like empty bottles, tubs, jars, envelopes or paper
Travel	*Taking fewer flights
	*Switching to public transport instead of driving for regular journeys
	*Switching to walking or cycling instead of driving for short, regular journeys
	*Driving in a fuel efficient way
Food	*Wasting less food
	*Buying fresh food that has been grown when it is in season in the country where it was produced
	Take your own shopping bag when shopping
	Decide not to buy something because it has too much packaging
Household	*Cutting down on the use of gas and electricity at home
	*Turning down thermostats (by 1 degree or more)
	Washing clothes at 40 degrees or less
	Making an effort to cut down on water usage at home
	Cut down on the use of hot water at home
	Leave your TV or PC on standby for long periods of time at home

* Dichotomous variables

Table 5: Goodness of fit indices for LCA models containing two-six classes

Model	ALMR p-value	Entropy
Two-class	0.00	0.786
Three-class	0.09	0.733
Four-class	0.01	0.754
Five-class	0.49	0.771
Six-Class	0.76	0.745

Table 6: Environmental class probabilities for four-class model

	N	Class %
Class 1: Pro-environmental	841	28.7%
Class 2: Neutral Majority	1,072	36.6%
Class 3: Paradoxical	471	16.1%
Class 4: Disengaged	544	18.6%
Total	2,928	100

Table 7: Multinomial regression to show variations in age, gender and SES by environmental class membership.

Co-variates*	Pro-environment				Neutral Majority				Disengaged				Paradoxical			
	N	%	*RRR*	*CI*	N	%	*RRR*	*CI*	N	%	*RRR*	*CI*	N	%	*RRR*	*CI*
Age*																
16-24	53	18.15%	1	1.00,1.00	96	32.88%	-	-	64	21.92%	1	1.00,1.00	79	27.05%	1	1.00,1.00
25-34	114	26.57%	1.51	0.82,2.80	161	37.53%	-	-	65	15.15%	0.94	0.51,1.73	89	20.75%	0.77	0.43,1.37
35-44	156	29.05%	1.87	1.02,3.43	223	41.53%	-	-	71	13.22%	0.56	0.30,1.05	87	16.20%	0.48	0.27,0.85
45-54	157	30.97%	2.16	1.17,3.99	192	37.87%	-	-	79	15.58%	0.56	0.29,1.07	79	15.58%	0.45	0.25,0.84
55-59	84	36.68%	2.51	1.24,5.07	92	40.17%	-	-	30	13.10%	0.37	0.15,0.93	23	10.04%	0.24	0.10,0.61
60+	277	29.66%	2.53	1.35,4.76	308	32.98%	-	-	235	25.16%	0.91	0.49,1.72	114	12.21%	0.41	0.22,0.79
Total	841	28.72%	-	-	1072	36.61%	-	-	544	18.58%	-	-	471	16.09%	-	-
Gender*																
Male	399	27.75%	1	1.00,1.00	512	35.61%	-	-	309	21.49%	1	1.00,1.00	218	15.16%	1	1.00,1.00
Female	442	29.66%	0.91	0.69,1.20	560	37.58%	-	-	235	15.77%	0.47	0.32,0.69	253	16.98%	0.94	0.67,1.34
Total	841	28.72%	-	-	1072	36.61%	-	-	544	18.58%	-	-	471	16.09%	-	-
Social Grade*																
Retired/unemployed/low grade workers	115	23.76%	1	1.00,1.00	140	28.93%	-	-	127	26.24%	1	1.00,1.00	102	21.07%	1	1.00,1.00
Semi-skilled workers	97	24.37%	0.44	0.22,0.89	143	35.93%	-	-	81	20.35%	0.37	0.17,0.82	77	19.35%	0.49	0.23,1.01
Skilled manual workers	147	24.66%	0.62	0.33,1.16	226	37.92%	-	-	129	21.64%	0.76	0.38,1.49	94	15.77%	0.57	0.29,1.14
Supervisory	226	28.86%	0.67	0.37,1.22	314	40.10%	-	-	124	15.84%	0.55	0.29,1.06	119	15.20%	0.52	0.27,1.01
Intermediate managerial	209	37.32%	0.65	0.34,1.24	218	38.93%	-	-	69	12.32%	0.42	0.19,0.90	64	11.43%	0.56	0.26,1.20
Higher managerial	47	43.93%	1.41	0.57,3.45	31	28.97%	-	-	14	13.08%	0.84	0.24,2.90	15	14.02%	1.98	0.63,6.29
Total	841	28.72%	-	-	1072	36.61%	-	-	544	18.58%	-	-	471	16.09%	-	-
Highest Qualification*																
No Formal Qualifications	137	30.11%	1	1.00,1.00	155	34.07%	-	-	90	19.78%	1	1.00,1.00	73	16.04%	1	1.00,1.00
A/O levels	258	27.56%	0.6	0.41,0.87	337	36.00%	-	-	146	15.60%	0.4	0.25,0.63	195	20.83%	0.83	0.54,1.29
Degree level	256	38.91%	0.65	0.42,0.99	269	40.88%	-	-	76	11.55%	0.47	0.28,0.79	57	8.66%	0.69	0.41,1.18
Total	651	31.77%	-	-	761	37.14%	-	-	312	15.23%	-	-	325	15.86%	-	-
Household Income*																
10000 – 19000	253	27.41%	1	1.00,1.00	301	32.61%	-	-	200	21.67%	1	1.00,1.00	169	18.31%	1	1.00,1.00
20,000 – 39,000	174	28.11%	1.17	0.79,1.72	250	40.39%	-	-	86	13.89%	0.97	0.60,1.57	109	17.61%	1.21	0.77,1.90
40,000 – 50,000	140	33.41%	1.35	0.88,2.07	172	41.05%	-	-	51	12.17%	0.71	0.40,1.27	56	13.37%	0.33	0.18,0.61
Total	567	28.91%	-	-	723	36.87%	-	-	337	17.19%	-	-	334	17.03%	-	-

* chi2 p<0.05

Table 8: Binary logistic regression to show the relationship between environmental class membership and each pro-environmental behaviour individually.

	Measure of Behaviour (outcome)	Pro-Environment		Neutral Majority		Paradoxical		F†
		AOR	CI	AOR	CI	AOR	CI	
Travel	Taking fewer flights	2.62***	1.90,3.62	1.48*	1.08,2.03	1.33	0.93,1.90	6.30**
	Driving in a fuel efficient way	1.4	0.91,2.15	1.07	0.72,1.57	0.64+	0.41,1.01	6.88**
	Switching to public transport instead of driving for regular journeys	2.15***	1.48,3.11	1.67**	1.17,2.38	1.23	0.80,1.89	17.10**
	Switching to walking or cycling instead of driving for short, regular journeys	1.66**	1.19,2.31	1.28	0.94,1.74	0.88	0.61,1.26	3.20**
Home	Cutting down on the use of gas and electricity at home	2.41*	1.75,3.31	1.57*	1.18,2.08	0.94	0.69,1.29	7.80**
	Turning down thermostats (by 1 degree or more)	2.19*	1.64,2.94	1.62*	1.24,2.13	0.94	0.69,1.28	9.48**
	Wash clothes at 40 degrees or less	2.10***	1.39,3.15	1.42+	0.99,2.02	0.74	0.50,1.08	6.45**
	Make an effort to cut down on water usage at home	2.86***	2.17,3.75	2.24***	1.74,2.89	1.42*	1.07,1.89	12.38**
	Cut down on the use of hot water at home	1.89***	1.44,2.47	1.27+	0.99,1.63	0.86	0.64,1.14	9.50**
	Leave your TV or PC on standby for long periods of time at home	0.55***	0.42,0.73	0.66**	0.51,0.86	0.92	0.69,1.23	4.84**
Food	Checking whether the packaging of an item can be recycled, before you buy it	3.75***	2.76,5.09	2.10***	1.56,2.83	1.29	0.90,1.85	16.41**
	Take your own bag when shopping	1.86***	1.29,2.68	1.60**	1.15,2.22	0.78	0.55,1.12	17.07**
	Buying fresh food that has been grown when it is in season in the country where it was produced.	3.43***	2.61,4.51	2.15***	1.67,2.76	1.43*	1.07,1.91	16.28**
	How much effort do you and your household go to in order to minimize the amount of uneaten food you throw away?	4.31***	2.76,6.74	2.05***	1.45,2.91	1.08	0.74,1.58	9.91**
Recycling	Recycle items rather than throw them away	3.69***	2.26,6.04	2.39***	1.60,3.55	1.33	0.88,2.00	9.04**
	Reuse items like empty bottles, tubs, jars, envelopes or paper	2.95***	2.18,3.98	2.13***	1.63,2.80	1.07	0.80,1.43	10.12**

*p < 0.05 **prob > F

† F statistic is used to evaluate the null hypothesis that all of the model coefficients are equal to zero. A corresponding p-value indicates the probability of getting an F statistic as extreme as, or more so, than the observed statistic under the null hypothesis. This F test is equivalent to Wald's test or Likelihood ratio test.

6.4 Figures

Figure 1: Information criterion and log likelihood for one – six-class models

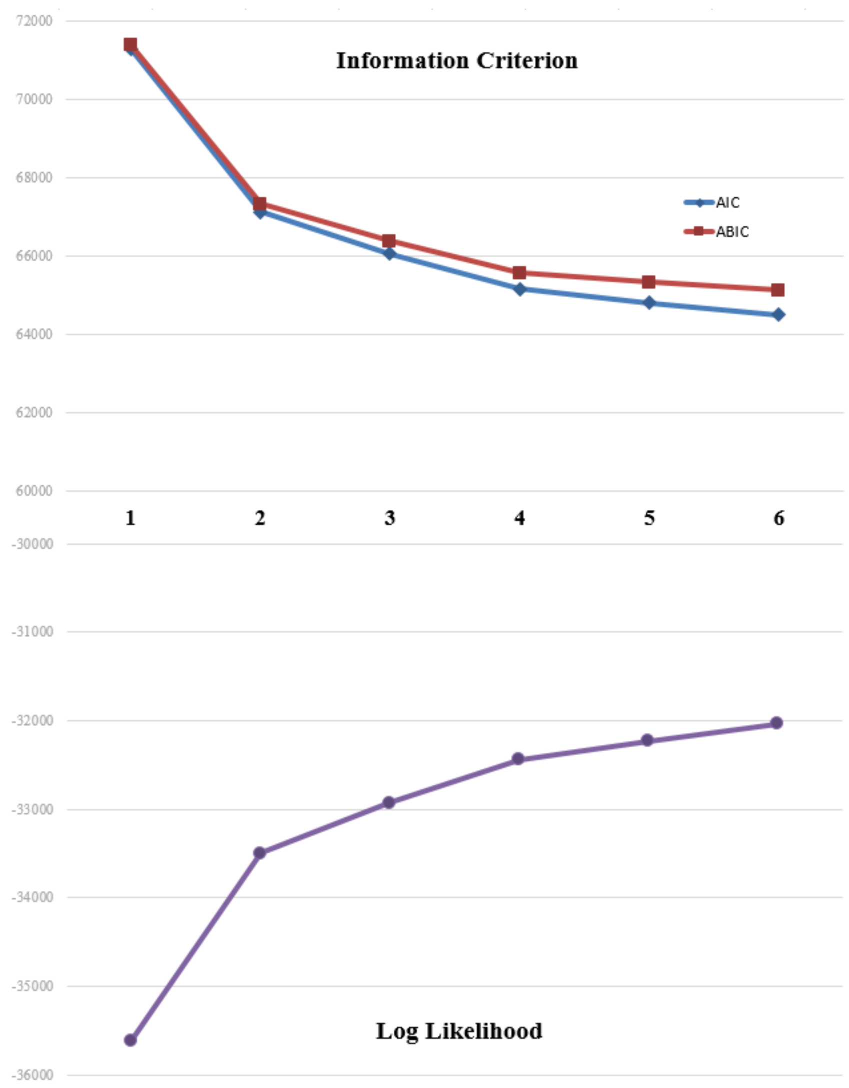

Figure 2: Item probabilities for the four-class LCA model

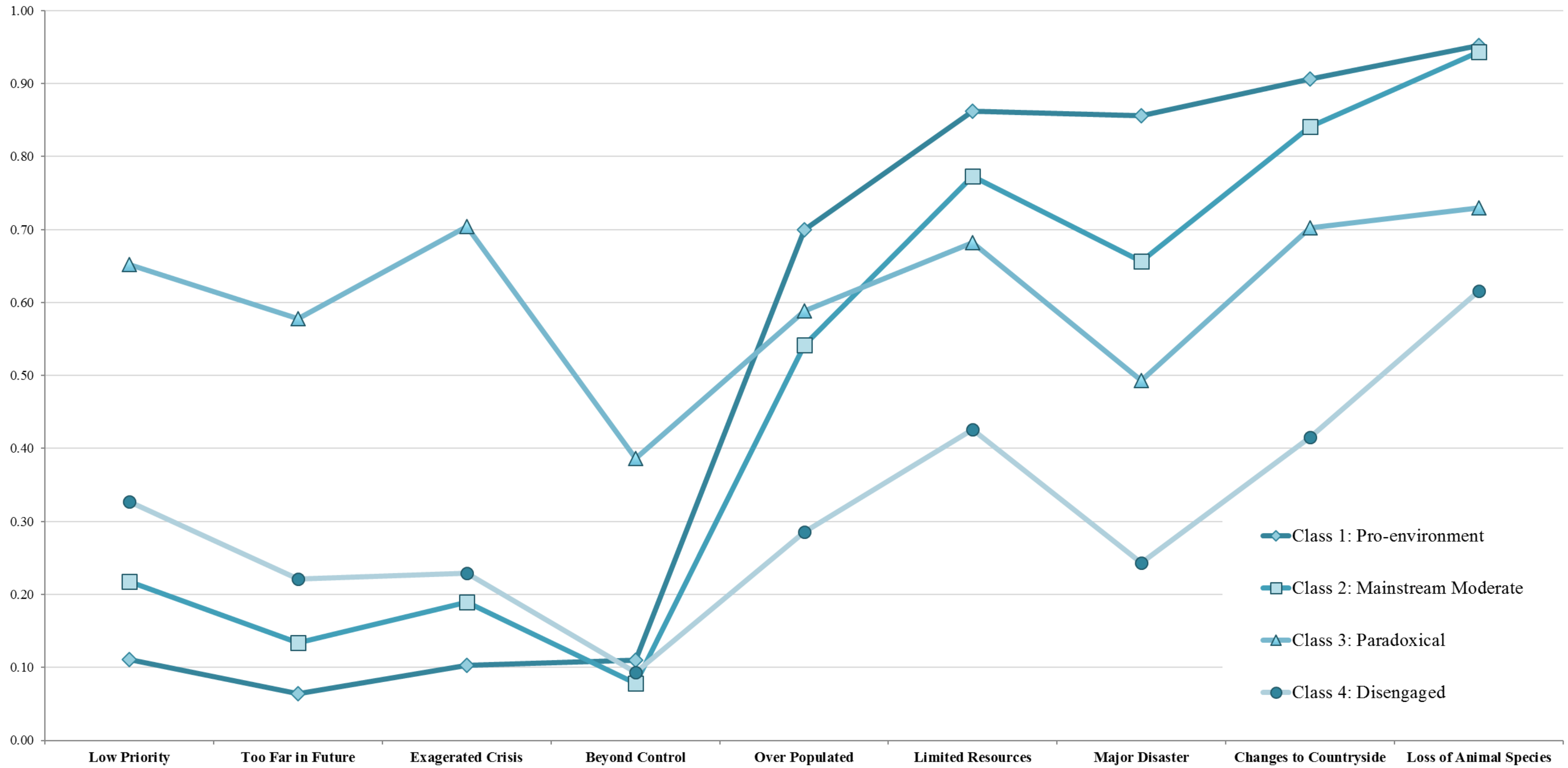

Figure 3: Relationship between the group structure extracted and a theoretical underlying dimension of environmental concern